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Abstract. Automatic optimization algorithms have been recently introduced as nonimaging optics design techniques. Unlike optimization of imaging systems, nonsequential ray tracing simulations and complex noncentered systems design must be considered, adding complexity to the problem. The merit function is a key element in the automatic optimization algorithm; nevertheless, the selection of each objective's weight, $\{w_i\}$, inside the merit function needs a prior trial and error process for each optimization. The problem then is to determine appropriate weights' values for each objective. We propose a new dynamic merit function with variable weight factors $\{w_i(n)\}$. The proposed algorithm automatically adapts weight factors during the evolution of the optimization process. This dynamic merit function avoids the previous trial and error procedure by selecting the right merit function and provides better results than conventional merit functions. [DOI: 10.1117/1.OE.54.2.025107]

Keywords: optical optimization; dynamic merit function; nonimaging systems; dynamic weights.

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1 Introduction

Automatic optimization techniques have been recently introduced in the design of nonimaging systems.[1] Nonsequential ray trace tools and complex, noncentered, optical systems were the main impediments of extensive application of automatic optimization techniques to nonimaging optics problems. Nowadays, improvements in hardware and software capabilities allow the implementation of optimization utilities in software packages,[2,3] producing a powerful tool in the nonimaging design problem. The main steps in the nonimaging optimization procedure are (1) the parameterization of the optical system, including the definition of the constraints in the parameters; (2) the definition of the merit function (MF) to be minimized or maximized;[4] and (3) the selection of the optimization algorithm, for which the Nelder-Mead algorithm particularly produces a robust and convergent method in nonimaging optimization problem.[5]

In this paper, we focus our attention on the merit function, as it has the role to drive the optimization procedure; improvements in the capabilities of the merit function will improve the results of the optimization procedure. The most common way to build merit functions involves the weighted sum of squares of the differences between a set of objectives and their associated target values:[6]

$$\mathrm{MF} = \sum_i w_i (V_i - T_i)^2, \tag{1}$$

where w_i is the weight factor for the i'th objective, V_i is the value of the i'th objective, and T_i is the target value of the i'th objective. Equation (1) shows the direct influence of the weight factors on the MF and, therefore, on the optimization procedure. Commonly, the weights' factors $\{w_i\}$ are manually adjusted by a trial and error procedure;[7] this nonoptimal situation suggests the need to study methods for automatic adjustments of the weight factors $\{w_i\}$. In this paper, we propose a new type of merit function, dynamic merit function (DMF), which automatically adjusts the weight factors $\{w_i\}$ during the progress of the optimization procedure. The variation of weight factors modifies the optimization problem, and DMF becomes an effective optimization method.[8]

This work is organized as follows. Section 2 describes the DMF and the proposed algorithm. In Sec. 3, we apply DMF to a concentrating lens, a uniformizing lighting lens, a signaling light-emitting diode (LED) collimator, and a flat LED luminaire. In Sec. 4, the dependence of the DMF optimization on the complexity of the nonimaging system is analyzed. In Sec. 5, conclusions are given.

2 Dynamic Merit Function

For a nonimaging design, the most prevalent objectives to be optimized are efficiency, uniformity, angular emission, concentration factor, etc.,[7,9] and as a rule, all of them must be optimized at the same time. In this paper, efficiency and uniformity are selected as the objectives of the MF as they conform to two of the most typical parameters involved in nonimaging systems. The efficiency is measured by the flux reaching the detector screen divided by the emitted flux. The uniformity is calculated as the mean irradiance value divided by the maximum radiance at the detector screen:

$$\eta = \frac{\Phi_{\mathrm{detector}}}{\Phi_{\mathrm{emitted}}}, \qquad U = \frac{\bar{E}}{E_{\max}}. \tag{2}$$

But the right balance between each one of these objectives in the optimization procedure and the right choice of the merit function is still a trial and error process[10] which depends on the particular problem to be considered. To

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avoid this misfunction, we propose a DMF which automatically modifies the weight of each objective $\{w_i(n)\}$ as the optimization procedure advances.

$$\mathrm{DMF} = 2 - [w_\eta(n)\eta + w_U(n)U] \\ = 2 - \{\lambda(n)\eta + [2-\lambda(n)]U\}, \quad (3)$$

where η is the efficiency of the system and U is the uniformity, w_η is the weight factor for efficiency and w_U is the weight factor for uniformity, n is the iteration number of the DMF optimization, and λ defines the constraint that the weight factors must accomplish:

$$w_\eta(n) + w_U(n) = 2, \quad w_\eta(n) = \lambda(n), \quad w_U(n) = 2 - \lambda(n), \\ \lambda(n)\epsilon[0{,}2]. \quad (4)$$

The Nelder-Mead algorithm is employed to accomplish the optimization. This numerical method, based on the simplex concept,[11] is a commonly used technique for minimizing a nonlinear multiobjective function. The simplex-based algorithm has proven to be a suitable method for illumination system optimization since the MF derivate is not employed. The noise inherent in the ray tracing analysis may introduce an appreciable variation in the MF magnitude at each simulation.[12]

The optimization process becomes a minimization problem and the DMF decreases as the objectives (η, U) increase [Eq. (3)]. The DMF optimization begins with a uniform weight $w_\eta = w_U = 1$ and revises these values for every conventional optimization cycle.

The conventional merit function (CMF) is composed of fixed weight values. A unique DMF iteration comprises several CMF iterations denoted by m index (Fig. 1). The CMF concludes under two self-contained conditions: the first condition is met if the CMF iteration m reaches its maximum value (M), and the second condition is specified by means of the tolerance parameters which establish the minimum variation of the MF and optimization's variables. The variations of the MF and the optimization variables have to be simultaneously lower than each tolerance parameter (respectively) to end the CMF optimization.

The algorithm, aimed at balancing the weight of each objective, compares the obtained values of both objectives

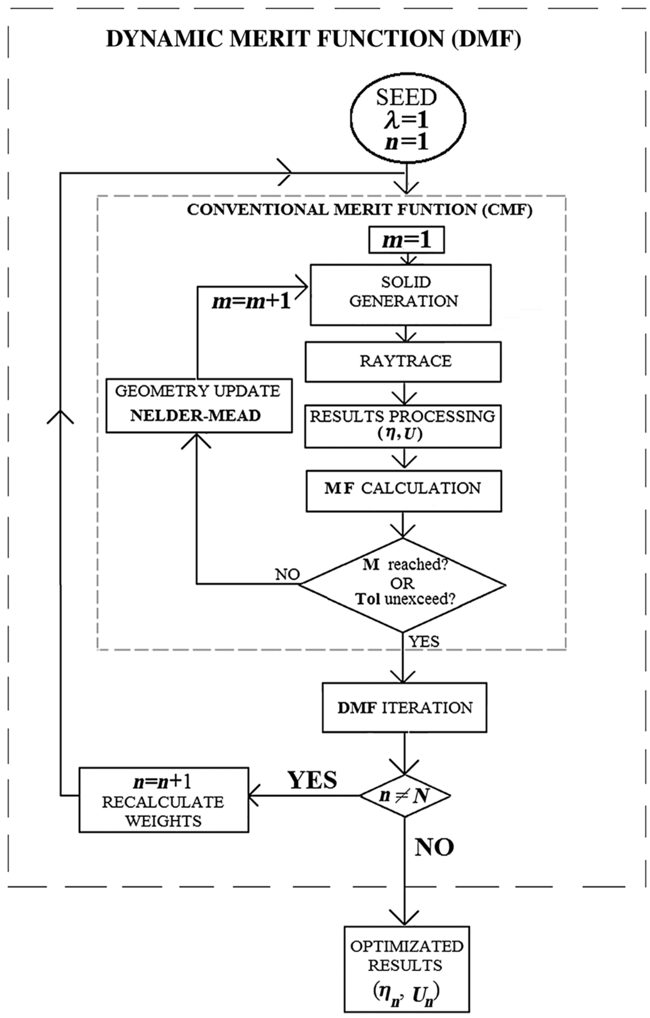

Fig. 1 Flux diagram of dynamic merit function (DMF) optimization.

$[\eta(n),\ U(n)]$, adds a quantity D/n to the weight factor of the lower objective and subtracts the same value from the upper objective:

$$\left\{\begin{array}{l} \text{if } [\eta(n) > U(n)] \Rightarrow w_\eta(n+1) = w_\eta(n) - \frac{D}{n}, w_U(n+1) = w_U(n) + \frac{D}{n} \\ \text{if } [U(n) > \eta(n)] \Rightarrow w_\eta(n+1) = w_\eta(n) + \frac{D}{n}, w_U(n+1) = w_U(n) - \frac{D}{n} \end{array}\right\}, \quad (5)$$

or its equivalent constraints equation:

$$\left\{\begin{array}{l} \text{if } [\eta(n) > U(n)] \Rightarrow \lambda_\eta(n+1) = \lambda_\eta(n) - \frac{D}{n} \\ \text{if } [U(n) > \eta(n)] \Rightarrow \lambda_\eta(n+1) = \lambda_\eta(n) + \frac{D}{n} \end{array}\right\}, \quad (6)$$

where $D\epsilon(0,1)$.

As the DMF process advances (n index increases), the weight's variation (D/n) decreases, resulting in a convergent optimization algorithm of high accuracy.

3 Optimization of Nonimaging Devices

A study comparing conventional and dynamic merit functions is carried out to analyze the effectiveness of the DMF technique. Thus, the difference between conventional optimization and dynamic weights is presented. For this study, the following optical systems are selected: concentrating lens, uniformizing lighting lens, a signaling LED collimator, and a flat LED luminaire.

The light source employed for the concentrating lens is a 2×10^5 rays collimated random pattern, while the source employed for the uniformizing lighting lens, signaling LED collimator, and the flat LED luminaire is a Luxeon Rebel InGaN LED model of 5×10^5 rays.

The optimization objectives are measured at the detector screen. The detector subtends 5 deg in the concentrating lens and the signaling LED collimator cases, and a 60 deg angle from the uniformizing lighting lens and flat LED luminaire.

The matrix employed to process the results is 512×512 pixels in size.

The values reached by the objectives of our merit function should be balanced regardless of the difference between the contributions weighted by the merit function.[13] The variation of the weights follows a linear algorithm [Eq. (5)], which ensures the balance between the optimization objectives. The weight increment is set to D/n, where $D = 0.3$ and n is the DMF iteration index. The CMF tolerance parameters are set to 10^{-4}.

The maximum DMF iterations is set to $N = 3$, where each one is equivalent to multiple CMF iterations, and the execution time required depends heavily on this optimization parameter because the DMF requires N times the CMF execution time. This augment of time is worthwhile as long as the DMF achieves better results with a significant improvement of the objectives.

The improvement provided by the DMF compared to the CMF optimization is measured by the followings increment magnitudes:

$$\Delta\eta = (\eta_{\mathrm{DMF}} - \eta_{\mathrm{CMF}}), \quad \Delta U = (U_{\mathrm{DMF}} - U_{\mathrm{CMF}}),$$
$$\Delta\mathrm{MF} = \mathrm{MF}_{n=1} - \mathrm{MF}_{n=N}, \tag{7}$$

where η_{CMF} and U_{CMF} are the efficiency and uniformity objectives at the end of the last CMF iteration (iteration M), equivalent to the first DMF iteration ($n = 1$), and η_{DMF} and U_{DMF} are the efficiency and uniformity objectives at the end of the last DMF iteration (iterarion N). The increment of the normalized merit function, ΔMF, has also been calculated, considering the normalized weights $[w_\eta(n) = w_U(n) = 1]$ at the first and last DMF iteration.

It is a well-known fact that the initialization seed, which describes part of the algorithm's variables and the first configuration of the optical system, has a great influence on the optimization process. If different starting values lead to different solutions, then a multiple-restart strategy should be applied. The optimization process of each optical device presented in this paper follows a previous analysis of the initial values that define the system's geometry. The execution time involved in each optimization determines whether a large number of initial values or a more accurate search of an optimal initial configuration is recommended.[14]

The initial values for the following optimizations are chosen by means of a sampling process within the range of parameters that build an effective optical device. Each simulation process is executed considering several initialization values, and the final optimization process shown in this paper is the one that minimizes the merit function value. The influence of the set of starting values on the final result will be specified in each optimization conducted.

The DMF optimization process modifies the system's geometry to adapt its behavior to the dynamic change of the MF weights. The optimization variables are limited, by means of constraints, within a range that assures a realistic geometry that can be manufactured. There are two types of constraints: user constraints, based on designer criteria, and geometric constraints, which avoid geometrical concerns like facet overlapping or interference.

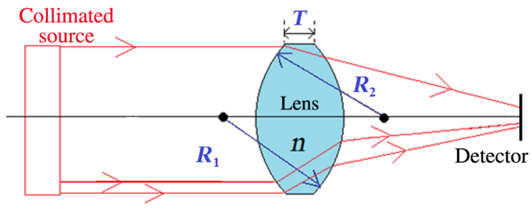

Fig. 2 Concentrating lens. Optimization variables: R_1, R_2, and T.

3.1 *Concentrating Lens*

In this section, the DMF optimization is applied to a biconvex concentrating lens, characterized by two radii (R_1, R_2), the refractive index n, and a thickness variable T (Fig. 2). The refractive index of the medium is $n' = 1$ (air). For the optimization process, three variables are chosen: R_1, R_2, and T. The feasible set of solutions is formed by the potential values, within a restricted interval, of these variables.

The initial configuration of the concentrating lens is set to $R_1 = 100$ mm, $R_2 = 200$ mm, $T = 1$ mm, and $n = 1.59$ (polycarbonate). This initial value is chosen as it provides the optimal results among the initialization seeds simulated, which includes a range of uniformity variation close to 24% and an efficiency variation <5.6%. The optimization process, starting from this configuration, reaches an optimal solution at the end of the third iteration (Fig. 3). The optimized variables of the concentrating lens are $R_1 = 92.4$ mm, $R_2 = 325$ mm, and $T = 3.2$ mm.

The DMF optimization applied to the concentrating lens (described by three variables) achieves an improvement of 13% in efficiency with a detriment of 34% of uniformity (Table 1) in comparison with the CMF optimization. Although the uniformity objective decreases through the DMF optimization, the final result is acceptable and it might be possible to reduce the uniformity loss if the rate of efficiency is not the priority. Another initialization seed considered for the concentrating lens leads to an improvement of 8% in efficiency with no loss of uniformity.

Each DMF iteration is graphically delimited by broken vertical lines (Fig. 3). If only one CMF optimization had been conducted, then the final result would not reach the optimal solution (in terms of efficiency) due to the effect of a local minimum in the merit function's feasible set of solutions. The lack of prospects of the conventional optimization to avoid the local minimum is precisely the main reason to address the DMF algorithm, which modifies the MF space and, thus, the distribution of the local minima.

Table 1 Dynamic merit function (DMF) results. Concentrating lens, uniformizing lens, and flat light-emitting diode (LED) luminaire.

System	$\Delta\eta$ (%)	ΔU (%)	ΔMF (%)
Concentrating lens (three variables)	13.6	−34.9	1.2
Uniformizing lighting lens (three variables)	19.5	9.5	12.7
Signaling LED collimator (three variables)	13.6	1.2	11.1
Flat LED luminaire (four variables)	24.3	6.1	13.9

MF, merit function.

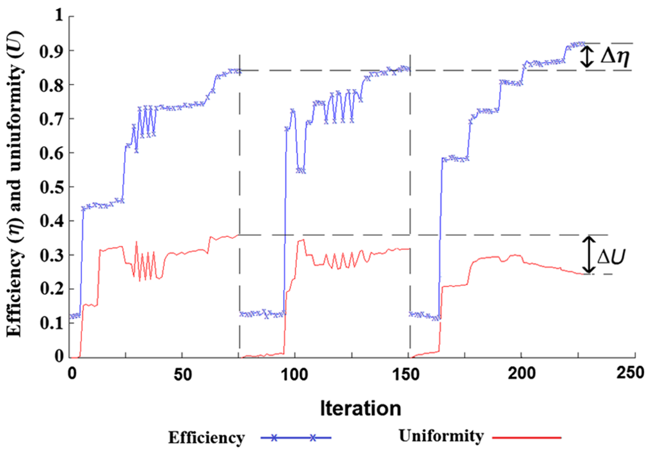

Fig. 3 DMF applied to three optimization variable concentrating lens.

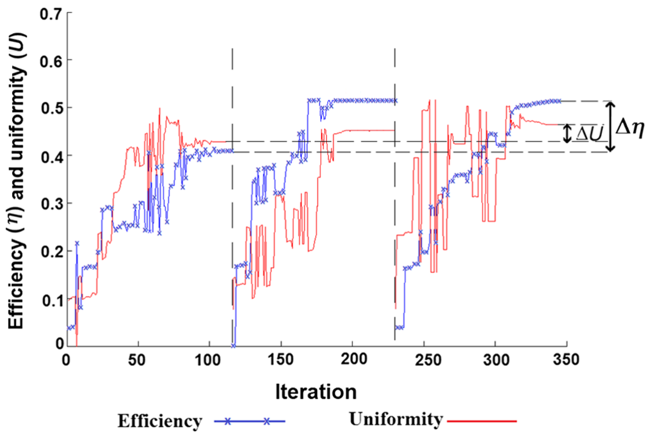

Fig. 5 DMF applied to three variable uniformizing lens.

3.2 *Uniformizing Lighting Lens*

The uniformizing lighting lens is an optical revolving geometry characterized by two radii (R_1, R_2), a height distance H, a thickness T, an aperture angle α and a refractive index n (Fig. 4). The first three parameters among them are chosen as optimization variables. This optical device is designed to achieve a batwing type emission, which ensures a greater rate of uniformity. The initial values for this devices are set to $R_1 = R_2 = 50$ mm and $H = 25$ mm. The initialization set of points studied involve a uniformity variation of 16.2% and efficiency variation of 10.6%

The uniformizing lighting lens is designed to provide a batwing emission pattern, which is usually employed in a lighting task.[15,16] However, not only a uniformity emission but also an efficient light flux transfer is a requirement for most lighting designs.[17] The need to reduce losses and, thus, obtain an efficient lighting system is the reason for employing the MF, where both efficiency and uniformity are included.

The dynamic optimization DMF demonstrates its effectiveness by increasing efficiency close to 30% and uniformity up to 9.5% (Table 1) compared to the CMF optimization applied to the same uniformizing lighting lens. The final configuration of the uniformizing lens ($R_1 = 63.7$ mm, $R_2 = 79.9$ mm, $H = 19.8$), achieved by the DMF optimization (Fig. 5), depends not only on the weight's factors but also on the algorithm's initial values. Depending on the initialization seed, the DMF process may take more or fewer iterations to achieve the best results, while this very factor is especially relevant within the CMF algorithm where it can determine its global effectiveness.

3.3 *Signaling LED Collimator*

In this section, an LED collimator will be optimized employing the DMF algorithm of the efficiency and uniformity objectives. Signaling LED collimators are usually included as source drivers in complex systems as beacon devices or LED luminaires. These global signaling systems are usually

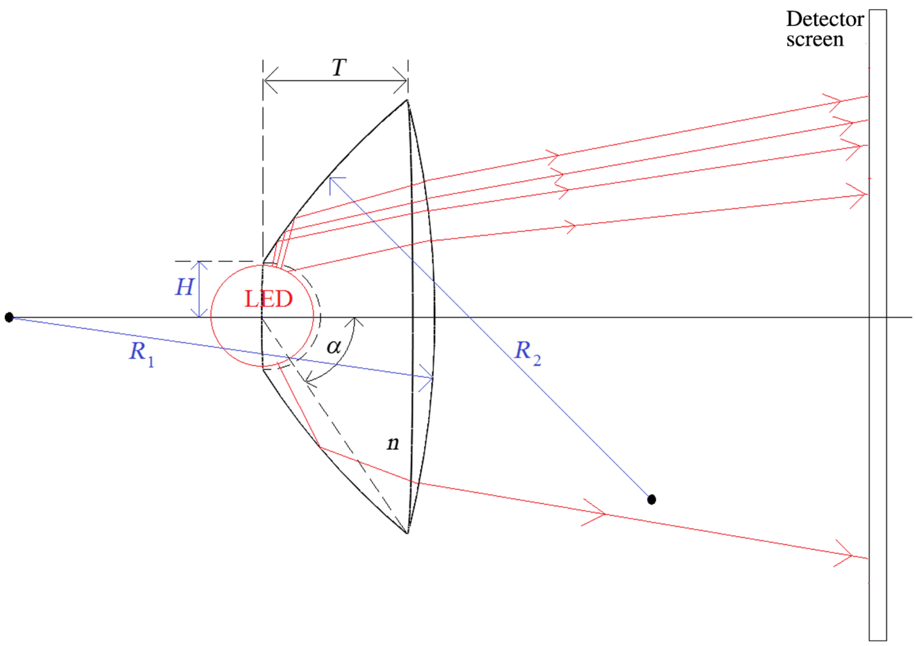

Fig. 4 Uniformizing lens. Optimization variables: R_1, R_2, and H.

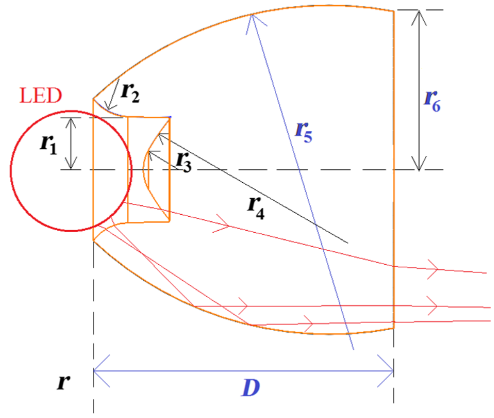

Fig. 6 Signaling light-emitting diode (LED) collimator. Optimization variables: D and the radii r_5 and r_6.

under demanding uniformity and efficiency requirements,[18] therefore, the MF employed is described by Eq. (3).

The collimator geometry can be described by: the LED coupling radius r_1; the entrance radii r_2, r_3, r_4; the total internal reflection (TIR) surface radius r_5; the output radius r_6; and the depth D. The optimization process will consider three variables: depth distance D, and the radii r_5 and r_6 (Fig. 6). The detector will consist of a plane that subtends 5 deg from the collimator, where the uniformity and the efficiency will be evaluated.

The initial values for these variables are set to $r_5 = 20$ mm, $r_6 = 8$ mm, and $D = 15$ mm. The optimization DMF of the signaling LED collimator provides an improvement of efficiency of 13.6% and a uniformity of 1.2% (Fig. 7), compared to the CMF optimization. The final configuration ends with the following variable values: $r_5 = 17.3$ mm, $r_6 = 9.3$ mm, and $D = 12.3$ mm.

3.4 *Flat LED Luminaire*

The dynamic optimization is now applied to a flat LED technology luminaire. This system is considerably more complex than the one previously analyzed. The luminaire is formed by an LED collimator of depth D (optimized in previous section) joined to a staggered duct that reflects the light to a micro-optic distribution matrix (TIR reflector based) described by the entrance radius R, the acceptance θ_1, and emission angle θ_2 (Fig. 8).

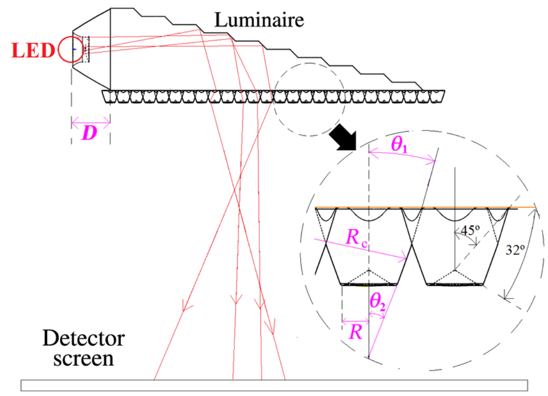

Fig. 8 Flat LED luminaire. Optimization variables: D, R, θ_1, and θ_2.

These magnitudes (D, R, θ_1, θ_2) are the variables of the DMF optimization. The initial values for the luminaire variables are $D = 12.3$ mm, $R = 2$ mm, $\theta_1 = \theta_2 = 12$ deg. The initialization set of points studied involve a uniformity variation of 36.2% and efficiency variation of 12.8%

The DMF optimization results (Fig. 9) show a great improvement ($\Delta\eta$ 25%, ΔU 6%) compared with the CMF results. This result confirms the suitability of the DMF optimization for complex systems. Optimized variables are established at following values: $D = 10.4$ mm, $R = 1.1$ mm, $\theta_1 = 15.3$ deg, $\theta_2 = 21.4$ deg.

It is also clear (Fig. 9) that the oscillation increases as the weight associated with the corresponding objective decreases. At the end of the first DMF iteration (delimited by first broken vertical lines), the efficiency is higher than the uniformity; therefore, the weight associated with the efficiency $[w_\eta(n)]$ is reduced by the DMF algorithm and the influence of efficiency [Eq. (3)] in the merit function is also reduced [Eq. (5)]. The oscillation effects of the objective with the highest weight (U), are becoming less relevant as it reaches a greater influence on the MF (Fig. 9). The Nelder-Mead tends to reduce the changes of the MF as it reaches an optimal solution. As the objective with the highest weight has a greater influence on the MF, its oscillations will be drastically minimized.

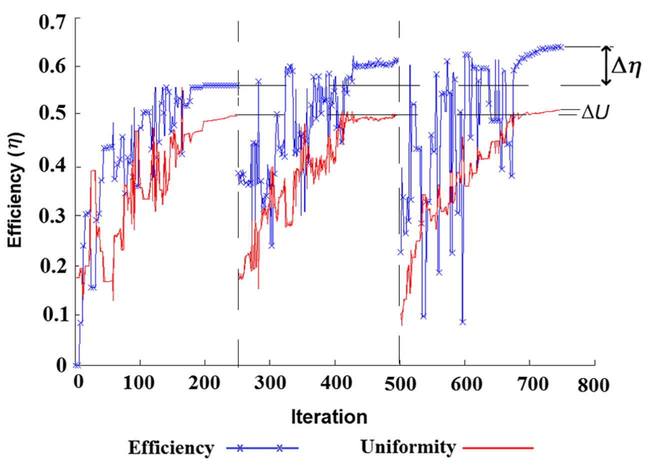

Fig. 7 DMF applied to three variable signaling LED collimator.

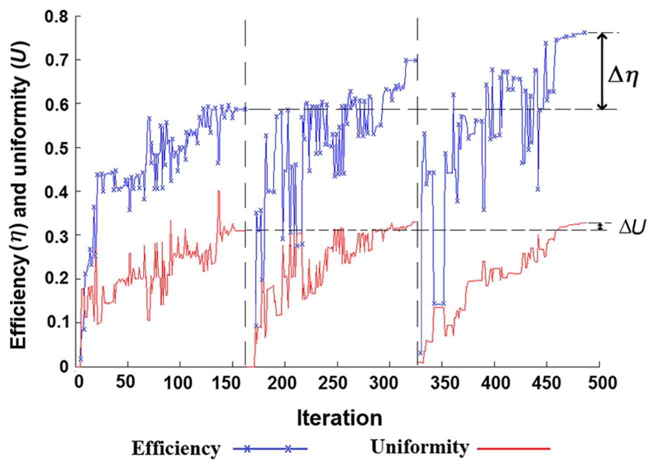

Fig. 9 DMF applied to four variable flat LED luminaire.

3.5 *Results of DMF Optimization Applied to Nonimaging Systems*

The DMF optimizations applied to the nonimaging devices that are considered imply an average relative change of 43% in the optimization variables. The results of previous optimizations are gathered in Table 1. It can be observed that the DMF optimization improves both uniformity and efficiency in most of the devices optimized.

4 Dependence of DMF on the Optimization Variables

The success of the optimization process depends on several factors, some of them related to the space variable that defines the solid geometry. The number of local minima in the merit function's space variable is proportional to the optical system's complexity; therefore, increasing the number of geometry parameters gives the DMF the capability to escape from the local minimum by modifying the solution space. To analyze the effect of the number of variables on the optimization results, the DMF will be applied to systems with different numbers of variables. These systems consist of a concentrating lens, a flat LED luminaire, and a signaling LED collimator.

For this occasion, the concentrating lens (Fig. 2) is optimized by considering two different configurations involving (1) two variables (R_1 and T) and (2) three variables (R_1, R_2, T).

It can be observed (Fig. 10) that the concentrating lens achieves no improvement (compared to CMF) if only two variables are considered, although this result depends on the initialization seed. On the other hand, the DMF applied to the three variable lens shows a notable improvement ($\Delta\eta$ 16%).

The signaling LED collimator device will be optimized taking into account the number of variables describing its geometry. On this occasion, two different DMF optimizations will be carried out depending on the number of variables describing the collimator: the first optimization will consider two variables, depth distance D and the radius r_5; the second optimization will choose the depth distance D and the radii R_5 and R_6 among the geometry variables (Fig. 6).

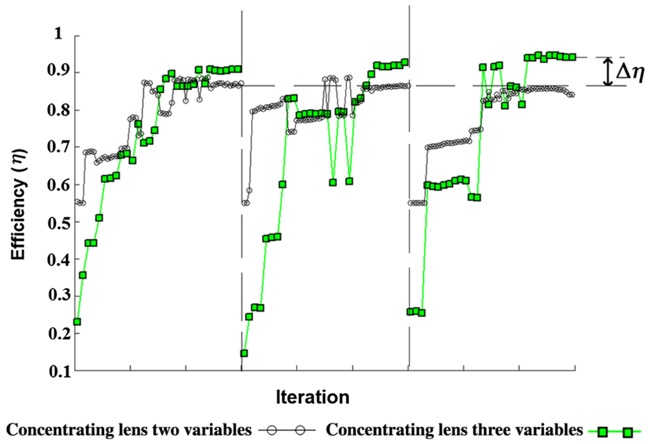

Fig. 10 DMF applied to two and three variables concentrating lens.

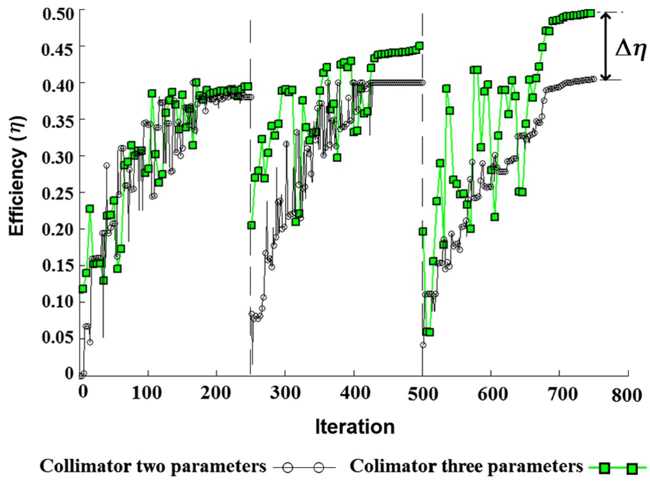

Fig. 11 DMF applied to two versus three variable signaling LED collimator.

The DMF optimization applied to two variables signaling the LED collimator achieves nearly identical results despite the MF weights' values that change in every CMF optimization (Fig. 11). The results achieved with a DMF process applied on the same collimator but provided with an additional degree of freedom (three variables) show a notable improvement in terms of efficiency (22.4%) (Table 2) regarding the CMF optimization. DMF optimization, applied to a three variables collimator, improves over the initial static weights optimization, since the DMF optimization changes the minimum distribution on the variable space.

The flat LED luminaire is continued considering two and three optimization variables and comparing the results with previous (four variables) luminaire optimization. The two variables optimization chooses the collimator depth D and the reflector radius R (Fig. 8) as variables. The three variables optimization also considers the emission angle θ_2. The graphical representation of the optimization considering three variables is not shown in Fig. 12 because with the large number of oscillations of the three overlapping curves, it would be difficult to discern each optimization process individually.

The DMF obtains better results (Fig. 12) compared to CMF optimization as the luminaire is described with a higher number of variables. The four variables DMF optimization achieves an improvement of $\Delta\eta = 24.3\%$ and $\Delta U = 4.1\%$ compared to the two variables luminaire (Table 2).

Table 2 DMF results. Influence of the number of variables.

System	$\Delta\eta$ (%)	ΔMF (%)
Concentrating lens (two versus three variables)	16	13.1
Collimator (two versus three variables)	22.4	27.3
Luminaire (two versus three variables)	6.1	5.3
Luminaire (two versus four variables)	24.3	18.8

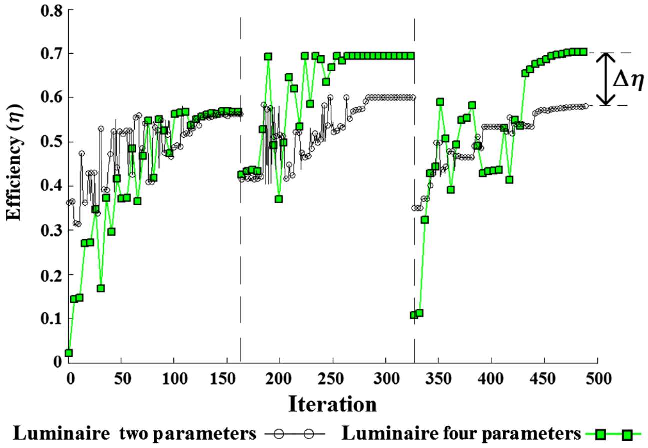

Fig. 12 DMF applied to two versus four variable flat LED luminaire.

5 Conclusions

A new optimization method has been proposed based on variable merit function. The weight of each objective inside the merit function is automatically adjusted by an algorithm as the optimization process advances. This new DMF avoids the trial and error process in the selection of the weight's factor and provides better optimization results than the CMF. The DMF optimization method has the capability to reduce the effect of the local minimum, modifying the space of solutions and improving the result of the process. The DMF algorithm has been applied to four standard nonimaging systems (concentrating lens, uniformizing lighting lens, signaling LED collimator, and flat LED luminaire), improving by ~25% the efficiency and with a 10% mean uniformity improvement in comparison with CMF. The dependence of the DMF optimization method on the number of optimization variables in the nonimaging optical system has been analyzed. In these samples, DMF provides better results for systems with a greater number of optimization variables, which could mean that DMF is a suitable method for designing complex optical systems.

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